

An Adaptive-Network-Based Fuzzy Inference System for Project Evaluation^{1*}

Sistema de inferencia borroso basado en redes adaptativas para la evaluación de proyectos²

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Abstract

In this article, a set of key management indicators related to performance of execution, planning, costs, effectiveness, human resources, data quality, and logistics, are considered for the evaluation of a project. Several automated tools support project managers in this task. However, these tools are still insufficient to accurately assess projects in organizations with continuous improvement management styles and with presence of uncertainty in the primary data. An alternative solution is the introduction of soft computing techniques, allowing gains in robustness, efficiency, and adaptability in these tools. This paper presents an adaptivenetwork-based fuzzy inference system (ANFIS) to optimize projects evaluation made with the Xedro-GESPRO tool (manufacturer: Universidad de las Ciencias informáticas, [20], versión: 14.05, Cuba). The implementation of the system allowed the adjustment of fuzzy sets parameters in the inference rules for the assessment of projects, based on the automatic calculation of indicators. The contribution of this research lies in the application of ANFIS soft computing technique to optimize the evaluation of projects integrated with the management tool. The results contribute to the improvement of existing decision-making support tools into organizations towards project-oriented production.

Keywords

ANFIS; decision-making; fuzzy inference system; project evaluation; soft computing

Resumen

Con el propósito de evaluar un proyecto, en este artículo se analizan unos indicadores clave de gestión como índices de rendimiento de la ejecución, planificación, costos, eficacia, recursos humanos, calidad del dato y logística. Diversas herramientas informáticas asisten a los directores de proyectos en este sentido; sin embargo, aún son insuficientes ante la precisión con que proponen la evaluación de proyectos en organizaciones con mejora continua en los estilos de gestión y presencia de incertidumbre en los datos primarios. Una alternativa es introducir técnicas de soft computing, lo cual permite ganar en robustez, eficiencia y adaptabilidad en las herramientas. El objetivo del trabajo consiste en desarrollar un sistema de inferencia borroso basado en redes adaptativas (ANFIS) para optimizar la evaluación de proyectos realizada con la herramienta Xedro-GESPRO. Mediante la aplicación de la propuesta se logra ajustar los parámetros de los conjuntos borrosos en las reglas de inferencia que permiten evaluar los proyectos a partir del cálculo automático de indicadores. La novedad del trabajo radica en la aplicación de la técnica de soft computing ANFIS para optimizar la evaluación de proyectos de forma integrada con la herramienta de gestión. El resultado alcanzado aporta al perfeccionamiento de herramientas de apoyo a la toma de decisiones existentes en organizaciones orientadas a la producción por proyectos.

Palabras clave

ANFIS; evaluación de proyectos; sistema de inferencia borroso; soft computing; toma de decisiones

Introduction

In order to manage work organizations align their production processes toward project management. A project is a set of processes consisting of collated activities with start and end dates defined to attain a goal, which can be related to obtaining a product or service. The proper application of knowledge, processes, skills, tools, and techniques has a significant impact on the success of projects [1]. A well-planned project, with evaluations by cut dates and study of alternatives, facilitates the tasks of management [2].

Competitiveness intensifies worldwide in the area of project management. Organizations require increasingly efficient planning of resources and activities, as well as their implementation and control, in order to achieve their objectives with quality in the least possible time. The execution control process is responsible for measuring, monitoring, and regularly evaluating the project progress through key performance indicators as to identify variances from the plan and take corrective action when necessary.

The execution control of projects is related with the management of numerical and linguistic data, noise caused by measurement errors, people's appreciation, and vagueness in concepts for decision-making. The shortcomings in the management of these data and incorrect evaluation of projects causes many economic losses with a high social impact. Some of the main causes of failure in this area include the lack of knowledge of good practices, little experience in control and monitoring of projects, as well as weaknesses in the tools for automatic or semiautomatic assessment of projects, and difficulties with the treatment of ambiguity and uncertainty of data [3].

Given the steady increase in the complexity to manage information related to project execution control, the use of computational tools is essential to assist managers in decision-making. Many such tools have been created in recent decades [4]. Although many meet the needs of their customers, not all of them provide solutions to the problems of machine learning in organizations with a continuous improvement in management styles and presence of uncertainty in

the raw data. Machine learning investigates the mechanisms by which knowledge is acquired through experience and is displayed as an interdisciplinary field which involves: statistics, logic, mathematics, neural structures, information theory, psychology, biology, artificial intelligence techniques, and soft computing [5].

An alternative solution in organizations to the aforementioned problems of machine learning is the introduction of soft computing techniques, which provide tools to approximate human reasoning through the use of knowledge and accumulated experience [6]. Under this principle, fuzzy systems, neural networks, evolutionary computing, probabilistic reasoning, as well as combinations thereof, are considered soft computing techniques [7]. Hybridization of various techniques of soft computing allows a gain in robustness, efficiency, adaptability, and proper balance between power prediction and interpretation [5]. Such techniques rely on the experience achieved in organizations, defined standards, results, and other types of knowledge, which are integrated and used to support decision-making.

Comparative studies of different machine learning strategies applied in decision-making show good results with Adaptive-Network-based Fuzzy Inference System (ANFIS) [8]. ANFIS is a machine learning strategy, presented by Jang (1993), which uses an algorithm inspired by the theory of neural networks to adjust the parameters of the rules of Sugeno-type fuzzy inference systems [9].

As in the case of project management, a significant amount of IT tools for soft computing technique application has been developed. The mathematical basis Matlab environment is one of the most widespread. It is used in engineering applications to analyze and develop prototype algorithms. Matlab facilitates the evaluation of various techniques without requiring the development of specific programs, using various toolboxes such as Fuzzy Logic [10]. The use or integration of these techniques with IT project management tools would provide them with the necessary functionalities for their use in environments with changing management styles and learning.

In recent years, several studies have suggested theoretical solutions based on specific applications of fuzzy logic and neural networks useful for project management [11]-[19]. However, the analyzed body of research does not integrate all the following characteristics: application of machine learning techniques; adjustment of the evaluation system according to continuous improvement in the organization management styles; and model integration with project management tools.

The Suite for Project Management Xedro-GESPRO has been developed by the Laboratory of Project Management Research of the University of Informatics

Sciences (UCI, by its acronym in Spanish) of Havana, Cuba. It is a generic and adaptable software ecosystem able to assist users in managing projects of any type of organization [20]. Among other scenarios, Xedro-GESPRO has been deployed in the network of production centers at the UCI as an integrated solution for managing the software projects the high learning center has set up. The computer system is aligned with the standards proposed by the Project Management Institute [1] and the Software Engineering Institute (SEI) [21], providing suitable interfaces for users to enter the information suggested by these models according to specific needs and levels of organizational maturity. Xedro-GESPRO allows the management of project portfolios, their respective schedules and monitoring progress. In [22], a model is proposed for project execution control using indicators and fuzzy logic solutions applied to the Xedro-GESPRO tool.

Despite all utilities provided by Xedro-GESPRO, there are drawbacks at the time of decision-making because information stored on rules that measure the indicators are static and do not suit every situation. To solve this problem, some investigations have been developed, such as [23], [24], where there is an integration of the application of machine learning techniques to the Xedro-GESPRO project management tool. While these two studies provide a solution to the problem of the integration of machine learning with project management tools, it is interesting to compare the results obtained to this point with other machine learning techniques in order to select the most appropriate one for each stage.

The aim of this work is to develop an ANFIS for optimizing the evaluation of projects using Matlab. This investigation reveals as a practical novelty the application of soft computing techniques, ANFIS especially, in the area of project evaluation. In the following sections we address the indicators used to evaluate projects and the fundamentals of neuro-fuzzy systems. Next, we show the flow of activities for the implementation of ANFIS in optimizing the evaluation of projects using Matlab. The article continues with the results of applying ANFIS to a set of training cases with indicators and assessment of projects retrieved from a database of completed projects managed with Xedro-GESPRO. Finally, conclusions are presented.

1. Materials and Methods

1.1. Indicators Used for Project Evaluation

In order to succeed during the execution of projects, it is essential to develop the leadership of a work team, where the main role as a leader is crucial, while

a set of indicators is being evaluated by cuts. These indicators should cover key knowledge areas of project management: cost, time, quality, logistics, and human resources. Indicators should be published as well by views, according to the different existing levels into the functional structure of the organization [2]. The most recognized standards and methodologies such as A Guide to the Project Management Body of Knowledge [1] and Capability Maturity Model Integration [21], reported the use of indicators as a key element from which control and monitoring of projects and organizations in general, is triggered. Among the most demanded indicators are those related to earned value, ROI, cost performance, schedule performance, human resources performance, logistics and quality. Some of these indicators are implemented for automatic calculation, especially in proprietary tools. Among the most representative project management tools worldwide [4], very few handle uncertainty in information, or provide reports and analysis when based on open source technology.

Automatic calculation of indicators for project management in organizations guarantees quality in the selection step, ensuring the consistency of data necessary for the initiation of automatic learning processes. The indicators used in this research to evaluate projects are related to the ones automatically calculated by the model of [22]; see Table 1.

| lable 1. Key indicators for | project management | calculated by | Xedro-GE24KO |
|-----------------------------|--------------------|---------------|--------------|
| | | | |

| Indicator | Knowledge area |
|--|----------------------------------|
| Execution Performance Index (IRE) | Scope and commitments management |
| Schedule Performance Index (IRP) | Time management |
| Cost Performance Index (IRC) | Cost management |
| Efficacy Performance Index (IREF) | Scope and quality management |
| Human Resources Performance Index (IRRH) | Human resources management |
| Logistic Performance Index (IRL) | Logistic management |
| Data Quality Index (ICD) | Information consistency |

Source: [22].

For the evaluation of the project, using the above indicators, a Sugeno-type Fuzzy Inference System (FIS) Zero Degree [25] is implemented. This system provides a base of 27 rules based on expert judgment for the evaluation. Trapezoidal membership functions used at the edges and triangular in the center, covering three fuzzy sets (low, medium, high) for each indicator. The working model of the FIS used Product as T-Norm and Maximum as T-conorm [22]. The current research

stems from this model, to which modifications have been made (explained in the "Results and Discussion" section) before applying the ANFIS technique for the adjustment of the parameters of fuzzy sets.

1.2. Neuro-Fuzzy Systems

The Neuro-Fuzzy Systems (NFS) use a combination of the paradigms of Fuzzy Logic and Artificial Neural Networks (ANN). On the one hand, the ANN pursue the simulation of human reasoning capabilities through their structure and organization, by taking advantage of their learning capacity and generalization ability. Meantime, the FIS allow expressing the knowledge of an "expert" human being by simple If-then rules described in natural language. The NFS arose from the need of obtaining and adjusting the FIS parameters, either their sets or rules, through a formal method not just based on human knowledge or on trial and error. The hybrid-type NFS present a unified architecture, being its foundation the interpretation of the rule base in terms of an ANN, where the input and output variables and the rules are seen as neurons of the model. For their application, a set of membership functions and initials fuzzy rules must be available, and also an error boundary that allows to stop learning.

1.3. Design of the Adaptive-Network-Based Fuzzy Inference System

ANFIS was one of the first hybrid type neuro-fuzzy models [26]. It is a Sugenotype FIS that uses a learning algorithm inspired by the theory of multilayer feed-forward neural networks to adjust the parameters of their membership functions. The current investigation takes as input-output pairs, or training data, the retrieved projects from a database of completed projects, with their corresponding calculated indicators and numerical evaluation. The antecedents of the rules are the fuzzy sets (low, medium, high) for each indicator shown in Table 1, and the consequents are the linear parameters from FIS output (numerical evaluation of the project).

Learning is divided into two stages, at first antecedents are set constant and learning is based on modifying the consequents by following the strategy of minimum squares, while in the second stage only antecedent parameters are modified by applying downward gradient. The antecedent membership functions require to be derivable. This two-stage approach improves the results obtained from the variant of only applying the downward gradient to optimize all parameters; it converges faster than backpropagation training used in the multilayer neural networks [26]. The adaptive capabilities of ANFIS networks make them

applicable to a lot of problems, where the classification data and the initial rule base is known, allowing the feature extraction from examples.

ANFIS uses a node-oriented multilayer network architecture in which the parameters of the membership functions reside within neurons and not in the weights of the connections. Node-oriented representation facilitates the FIS interpretation since its implementation. The network layers are not fully connected (all to all), but rather, the connections take place from the presence of the fuzzy rules and the relationships they represent within the FIS. The ANFIS designed for the problem of project evaluation has five layers. The changes during learning take place mainly in layers 1 and 4. The inputs to layer 1 are numerical values previously calculated for each indicator in Table 1. Each node of layer 1 calculates the membership degree of the value received to the fuzzy set it represents (low, medium, or high). Nodes of layers 2, 3, and 4 correspond to the 27 rules defined in [22]; these calculate and normalize activation and compute the output of the rule. The node of layer 5 computes the overall output of the system to display the numerical evaluation of the project.

1.4. Application of ANFIS to optimize project evaluation

For the optimization of project evaluation through application of ANFIS, the Fuzzy Logic toolbox of Matlab (The MathWorks, Inc., [10], Versión R2014a, Unite States) is used. This toolbox contains features that allow the adjustment of a FIS to obtain the optimized values of all modifiable parameters. To apply ANFIS it is necessary to know in advance the fuzzy inference rules of Sugeno Zero or One grade type system for the evaluation of projects, which will be subject to optimization.

Learning takes place from a set of training cases. Each case contains the numerical values of key performance indicators and project evaluations retrieved from a database of completed projects. These data are subjected to a process of selection, cleaning, and transformation in order to obtain a representative cases base. Data are divided into two sets: one for training and another for validating. Figure 1 shows the proposed process scheme for implementing ANFIS for the optimization of project evaluation using Matlab. The flow of activities allows designing and implementing several experiments as to adjust the fuzzy inference rules, compare the achieved results, and finally select the FIS to optimize the project evaluation.

Completed ANFIS Training and 3. Generate FIS using genfis2 or load preconceived FIS 1. Execute anfisedit 2. Load training and validating dataset Editor validatina datase projects command dataset F۱ς Selected: optimization method. Dataset, FIS & projects 5. Train ANFIS error bound and iterations number training parameters evaluator FIS adjusted 6. Validate ANFIS with training Validation data Record training and FIS adjusted or validating dataset validating error Validation results Experiment (i) Organization <<Continuous improvement>>

Figure 1. Application of Adaptive-Network-based Fuzzy Inference System (ANFIS) to optimize project evaluation in an organization

Source: authors' own elaboration

Activity 1: The graphical interface to work with ANFIS, available in the Matlab Fuzzy Logic toolbox, is accessed through the anfisedit command. This interface allows you to create, train, and test a Sugeno-type FIS.

Activity 2: From the Anfis Editor interface, the set of cases of completed projects to be used for training and the set that will serve to validate the model of fuzzy inference optimization object are loaded.

Activity 3: The Anfis Editor interface allows loading a preconceived FIS, as it is case of the initial basis of rules defined in the model of Lugo et al. [22]. This interface also provides options to automatically generate the FIS to be optimized from a set of training cases (indicators and evaluations of completed projects) applying the genfis1 (Grid partition: through mesh partitioning of the data) and genfis 2 functions (Subtractive clustering: by pooling data). The use of the genfis 1 functionality is not convenient for the evaluation of projects through seven indicators (Table 1), as it creates a lot of rules that prevent training the FIS with ANFIS. Once the FIS is generated or loaded by the FIS Editor interface, its inputs, outputs, rules, fuzzy sets, membership functions, and aggregation method can be adjusted.

Activity 4: Training parameters are set: error bound, number of epochs, and optimization method. The latter may be the back-propagation or hybrid (minimum squares and downward gradient).

Activity 5: The action of training the ANFIS is performed from the training and validation sets, the FIS to be optimized and the training parameters, getting the FIS with the parameters of the fuzzy sets adjusted.

Activity 6: To validate, Matlab compares the output (numerical evaluation of projects) of the trained FIS with the expected output given by the validation set or training data itself. The check option offered by the ANFIS of Matlab allows stopping training in case of over-adjustment. For this, the scheme curves training error and validation error are examined. The over-training of the FIS is analyzed and parameters of fuzzy sets are selected just before the iteration where the validation error starts to rise and the training error decreases.

Activity 7: Validation and test errors committed during the FIS training should be stored in order to make a comparative analysis among several experiments performed, to optimize the FIS project evaluator.

Applying the above-described flow of activities is proposed to perform several experiments. In order to select the best suitable FIS for the optimization of project evaluation, a comparative analysis of the classifications obtained in each experiment with the adjusted FIS according to ANFIS and the expected output is performed. The metric used to measure the quality of classification or level of optimization in project evaluation is the predictive accuracy: number of projects correctly classified divided by the number of projects used in the validation of training. The most suitable experiment is the one that gets smaller training and validation errors and a higher predictive accuracy.

2. Results and Discussion

Through the use of the GUI to work with ANFIS in Matlab, 10 experiments are designed and implemented to optimize the fuzzy inference rules that execute the project evaluation. The knowledge base correspond to 204 completed projects provided by Xedro-GESPRO. In each case, values of the input (numerical values from indicators in Table 1) and output classification (final numerical evaluation of the project) given by a set of experts through Delphi method are known. The input and output data are normalized to values between 0 and 1.

2.1. Specifying parameters used in the experiments

In the first set of experiments the genfis2 functionality is used to generate the initial rule base by grouping the input-output data. Table 2 shows the parameters used in each experiment with the genfis2 function.

In the second half of the set of experiments, the Sugeno Zero Degree FIS of [22] is recreated in the Matlab environment. It has an initial base of 27 rules defined by expert judgment. All the experiments were run in a terminal with a Core Duo 1.86 GHz processor, 1 GB of RAM and Matlab. Forty iterations are applied with zero error tolerance and hybrid optimization method. To validate the training the option of testing with a different set of input-output pairs is used, applying a total of 122 instances for training and 82 for validating.

Table 2. Parameters used in the experiments with function genfis2

| Experiment | Range of influence | Squash factor | Accept ratio | Reject ratio |
|------------------|--------------------|---------------|--------------|--------------|
| Exp. 1, 2, and 3 | 0.50 | 1.25 | 0.50 | 0.15 |
| Exp. 4 | 0.15 | 1.25 | 0.15 | 0.01 |
| Exp. 5 | 0.08 | 1.25 | 0.08 | 0.06 |

Source: authors' own elaboration

2.2. Validation and Analysis of Results

In considering the scheme of training error curves and validation error, the parameters of fuzzy sets are determined just before the iteration where the FIS over-training occurs. Through the training and validation of FIS, the parameters of the fuzzy sets of the rules are adjusted. Once the experiments are applied, it is necessary to compare the results. In Table 3 training and validation errors are shown, which allows us to compare the performance of the 10 experiments performed to optimize the FIS project evaluator.

Table 3. Correlation of training parameters and errors obtained

| Experiment | Rules | Nodes | Membership functions | Average training error | Average validation error |
|------------|-------|-------|-------------------------|------------------------|--------------------------|
| Exp. 1 | 3 | 58 | Gaussmf | 4.158e-8 | 0.0002 |
| Exp. 2 | 3 | 58 | Gbellmf | 3.74e-8 | 5.093e-8 |
| Exp. 3 | 3 | 58 | zmf, gbellmf, smf | 3.379e-9 | 0.0002 |
| Exp. 4 | 48 | 778 | Gaussmf | 1.307e-6 | 0.0009 |
| Exp. 5 | 88 | 1418 | Gaussmf | 9.088e-7 | 0.001 |
| Exp. 6 | 27 | 106 | Gaussmf | 2.907e-9 | 3.176e-9 |
| Exp. 7 | 27 | 106 | Gbellmf | 3.002e-7 | 1.568e-5 |
| Exp. 8 | 27 | 106 | gauss2mf | 2.232e-6 | 0.0003 |
| Exp. 9 | 27 | 106 | zmf, gbellmf, smf | 7.066e-7 | 0.0009 |
| Exp. 10 | 27 | 106 | zmf, gaussmf, smf | 1.404e-6 | 0.0005 |

Source: authors' own elaboration

Experiment 6 obtained the best results with an average error equal to 2.907e-9 during training. The average validation error (3.176e-9) takes a lot better than the rest of the experiment values. The predictive accuracy metric (percentage of correctly classified projects) is applied to measure the quality of classification in project evaluation given by each experiment, yielding the results shown in Figure 2.

Quality of classification (%) 100 80 60 40 20 Exp. 1 Exp. 2 Exp. 3 Exp. 4 Exp. 5 Exp. 6 Exp. 7 Exp. 8 Exp. 9 Exp. 10

Figure 2. Comparison of projects correctly classified in each experiment

Source: authors' own elaboration

According to the data partitions (82 instances to validate) experiments 2, 3, 6, and 7 get the best predictive accuracy with 98.78% (81 well classified projects and just 1 wrong). The FIS obtained from Experiment 6 is selected as a classification model of new cases for evaluating projects since it attains the lowest training error, lower validation error, and higher predictive accuracy.

As result, an adaptive-network-based fuzzy inference system (provided by experiment 6) that optimizes project evaluation is obtained. To check the quality of the classification, a comparative analysis of results obtained by this NFS and the output given by the FIS of Lugo et al. [22] is performed against the expected output of the training cases (obtained by the Delphi method). From this analysis it is observed an improvement in the quality of the classification for project evaluation given by the NFS (98.78%) compared with the classification of FIS (80.48%). This means that the application of ANFIS succeeds in adjusting the parameters of the membership functions of fuzzy sets and thus, the evaluation of projects in Xedro-GESPRO.

The implementation of ANFIS in Matlab has the following limitations: It only supports FIS of Sugeno Zero or One Grade type; the membership functions of the antecedents require to be derivable; the membership functions of the consequents claim to be of the same type (linear or constant); the consequents are different for each rule; the FIS has only one exit; the rules have unitary weight;

and the initial base of rules must be known. However, the main advantage of using the ANFIS of Matlab is that an adjusted FIS can be obtained from a set of training data (pairs of input-output) without requiring its generation by a human expert; besides, it also allows validation learning. NFS integration with the project management tool is achieved through the export files option of Matlab. This .fis file is imported through functions implemented into the Xedro-GESPRO database. The file .fis contains the optimized parameters of the fuzzy sets of the rules. These data rules are stored in a table in the database and used every time the evaluation of new projects is done by the adjusted FIS. Once the FIS is trained, it is possible to introduce new projects and evaluate them properly. The proposed mechanism is valid to make the integration of ANFIS with any type of software project management tool.

Conclusions

Project evaluation is a complex task that involves vagueness in concepts and uncertainty in information, a situation where the use of soft computing techniques yields good results.

This paper shows the application of an ANFIS using the Matlab tool to optimize the rules that evaluate projects on Xedro-GESPRO. The developed adaptive-network-based fuzzy inference system allows the efficient adjustment of the existing rule base, increasing the quality of project evaluation. In addition, it makes it possible to preserve the knowledge of experts in organizations and to perform an effective control of project execution.

The application of ANFIS integrated with software project management tools as Xedro-GESPRO is a novel contribution, allowing raising the quality and competitiveness of the developed products, providing them with a high added value. The achieved result provides a contribution towards improving existing decision-making support tools into organizations to project-oriented production. Furthermore, the use of machine learning methods for the evaluation of projects increases the adaptability of organizations faced with the changing management styles caused by the maturity reached during their continuous improvement.

As future research we intend to work on different aspects such as the computational efficiency of the implementation of the ANFIS technique; the improvement of the optimization algorithm for calculating the fuzzy sets parameters; the incorporation of non-differentiable membership functions; and consideration of structural changes in the data. Also, the implementation of new machine learning libraries for the evaluation and control of projects with open source software tools and programing languages such as PL-R, opens a field of research related to the improvement of the integration with decision-making tools in project management.

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